Project ID: EEMS035

U.S. DEPARTMENT OF ENERGY
SMARTMOBILITY
Systems and Modeling for Accelerated Research in Transportation

Coupling Land-Use Models and Network-Flow Models

Paul Waddell, University of California Berkeley, LBNL
2019 VTO Annual Merit Review
June 11, 2019

Argonne National Laboratory | INL Idaho National Laboratory | Berkeley Lab | Oak Ridge National Laboratory | NREL National Renewable Energy Laboratory

OVERVIEW

Timeline

- Start date: 10/2017
- End date: 09/2019
- Percent complete: 85%

Budget

- Total funding: $0.69M
  - DOE share: 100%
- FY 2018: $0.26M
- FY 2019: $0.43M

Barriers

- Transportation planning overlooks long-term impacts on urban development, induced travel demand
- Computationally expensive transport models undermine long-term analysis
- Impact of new mobility technologies on long term household choices uncertain

Partners

- Project Lead: LBNL
- Partners: LBNL, NREL, ORNL, INL, ANL
- Collaborators: Google, Purdue, UT Austin, MTC

RELEVANCE

- Need to quantify the impact of urban development on mobility patterns and energy use
- Need to quantify the impacts of SMART technologies on long-term urban development
- Need to evaluate combined policy impacts of land use and transportation to avoid endogeneity bias
- Supports EEMs/VTO Goal: Linking long-term modality styles with short/medium term mode choice in a multimodal transportation system, with the ability to simulate emerging mobility services.

RELEVANCE

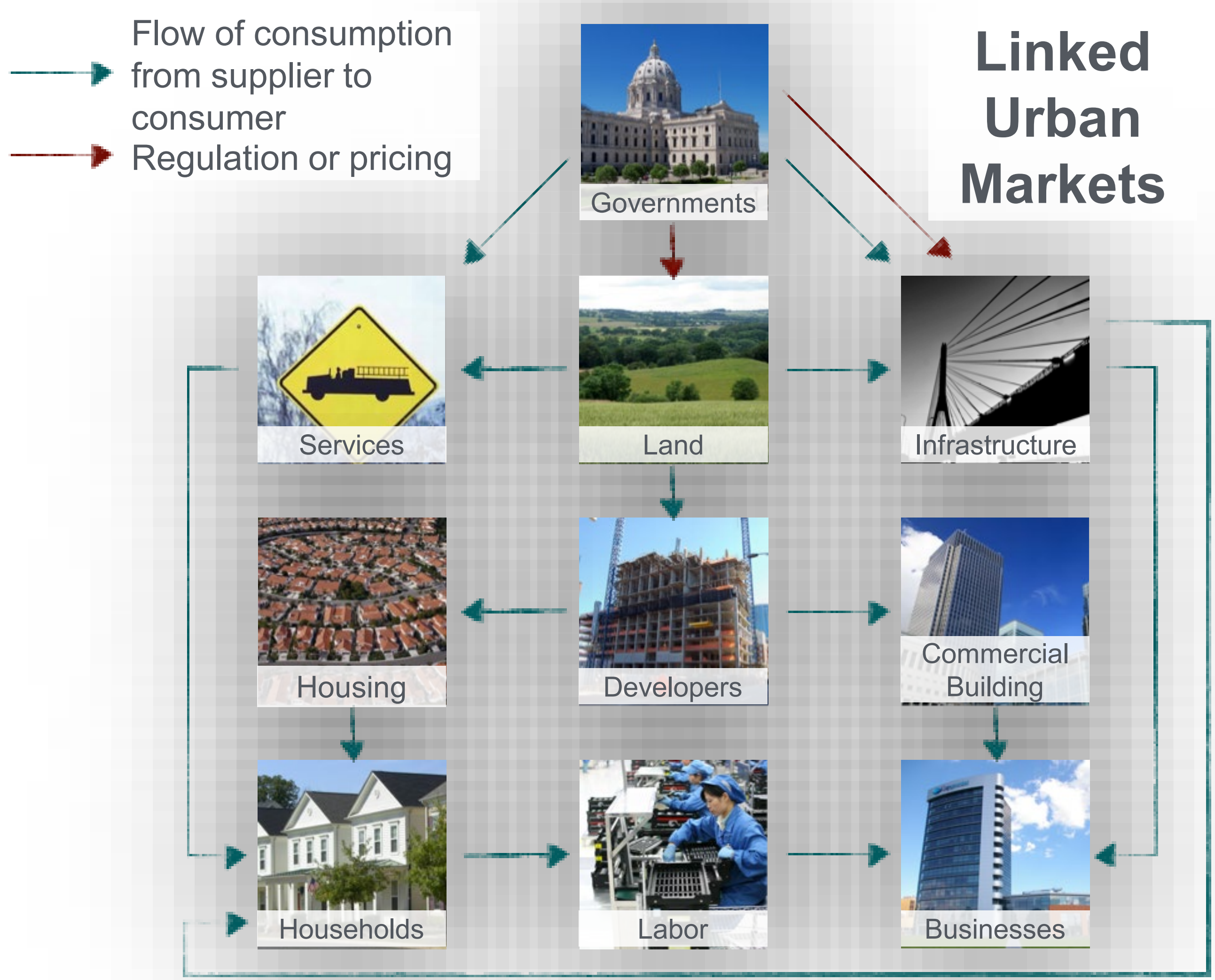
Overall Objectives

- Develop an integrated modeling pipeline that encompasses land use, travel demand, traffic assignment, and energy consumption
- Model combined and cumulative impacts of transportation infrastructure and land use
- Improve computational performance to simulate regions over 30 years for scenario analysis

Specific Objectives this Period

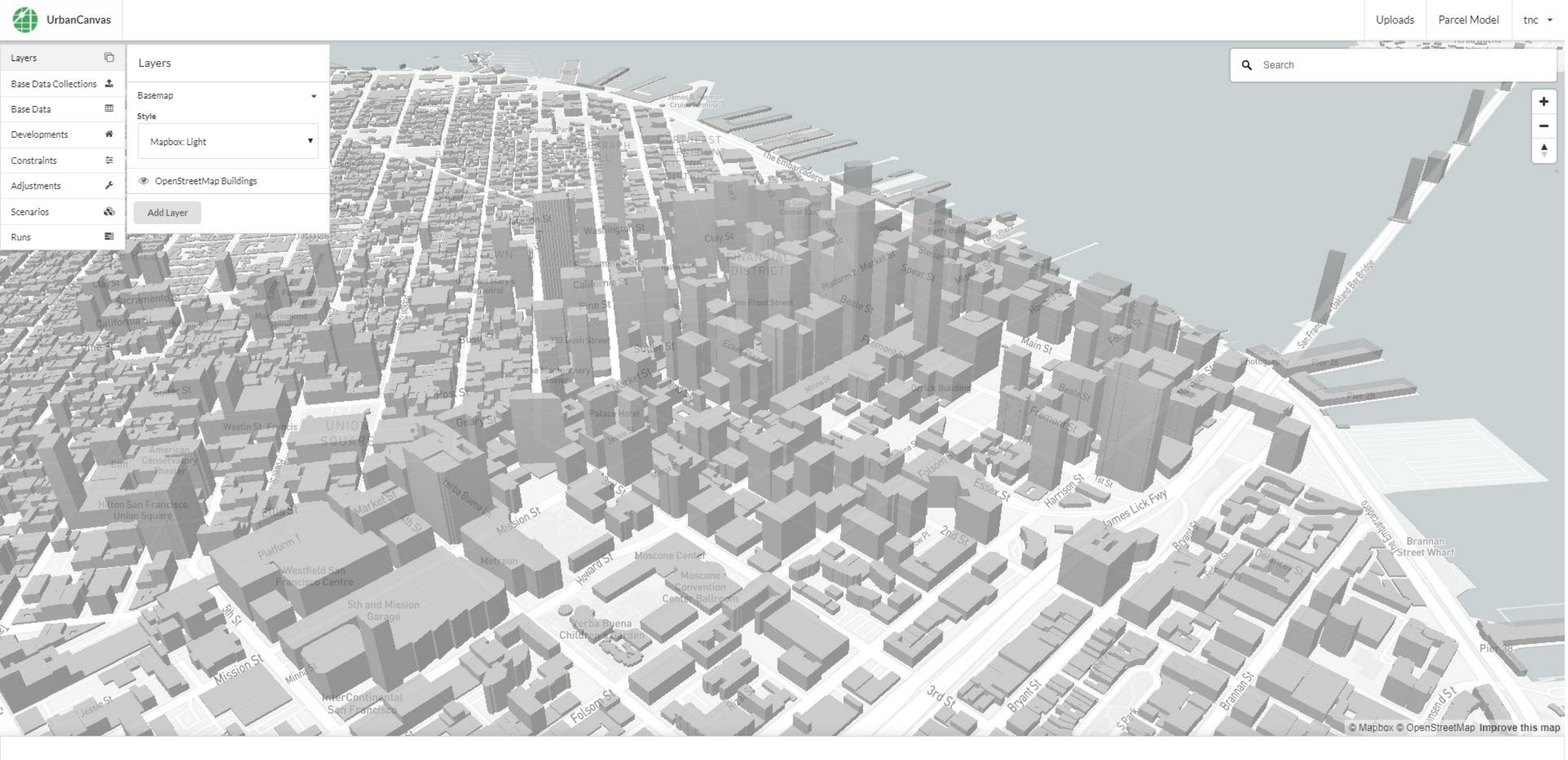
- Develop preliminary activity generation and scheduling to create inputs to BEAM
- Incorporate generalized costs in UrbanSim land use models to add sensitivity to scenarios modeled in BEAM
- Conduct preliminary benchmarking
- Develop conference papers and journal articles to publish progress

PRIOR WORK: UrbanSim



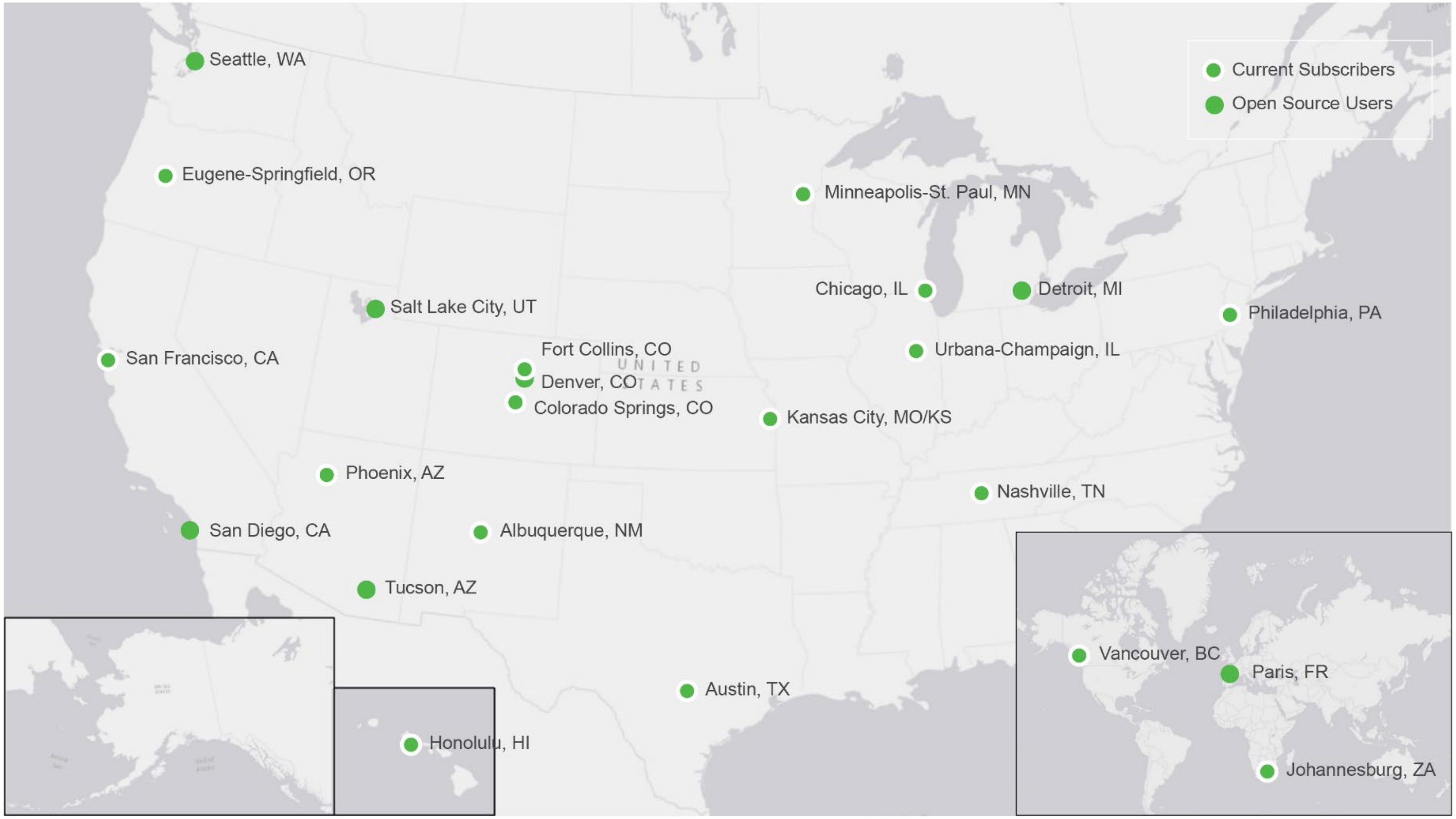
PRIOR WORK: TECHNOLOGY TRANSFER

UrbanCanvas developed by UrbanSIm Inc. as cloud platform to accelerate UrbanSim adoption by Metropolitan Planning Organizations (MPOs)



PRIOR WORK: TECHNOLOGY TRANSFER

**UrbanSim is Growing Rapidly in Adoption by MPOs:
Coverage expanded from 6 million population to over 60 million since 2016**

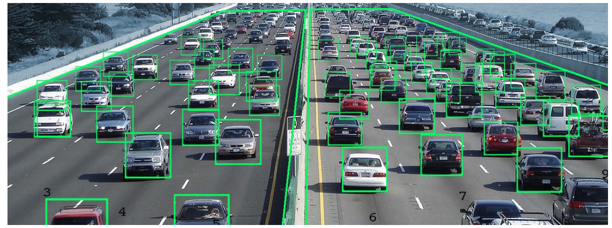


MILESTONES

Date	Milestone	Status
September 2018	Initial implementation of ActivitySynth (daily activity demand generation for mandatory trips)	Complete
March 2019	Performance evaluation of integrated modeling platform, identify opportunities for improvement of computational efficiency and predictive power.	Complete
June 2019	Progress measure: Run UrbanSim and BEAM end-to-end on 2+ scenarios in Bay Area and produce a portfolio of metrics	On track
September 2019	Evaluate implementation of the platform for potential application to additional metro areas (e.g. Denver, Chicago, Columbus) depending on travel model availability.	On track

APPROACH

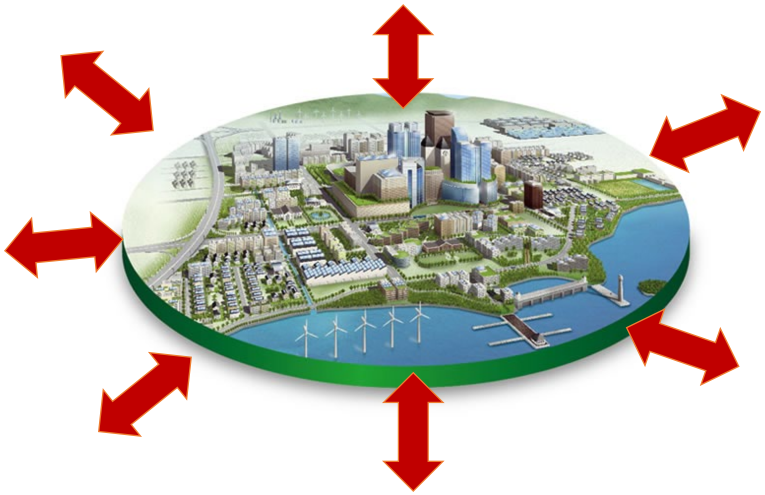
New Forms of Mobility



Enhanced Traffic Flow

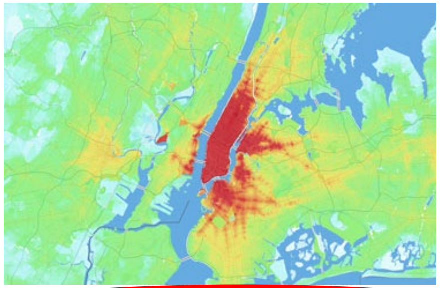
Vehicle Ownership / Vehicle Energy Performance

Traveler Behavior



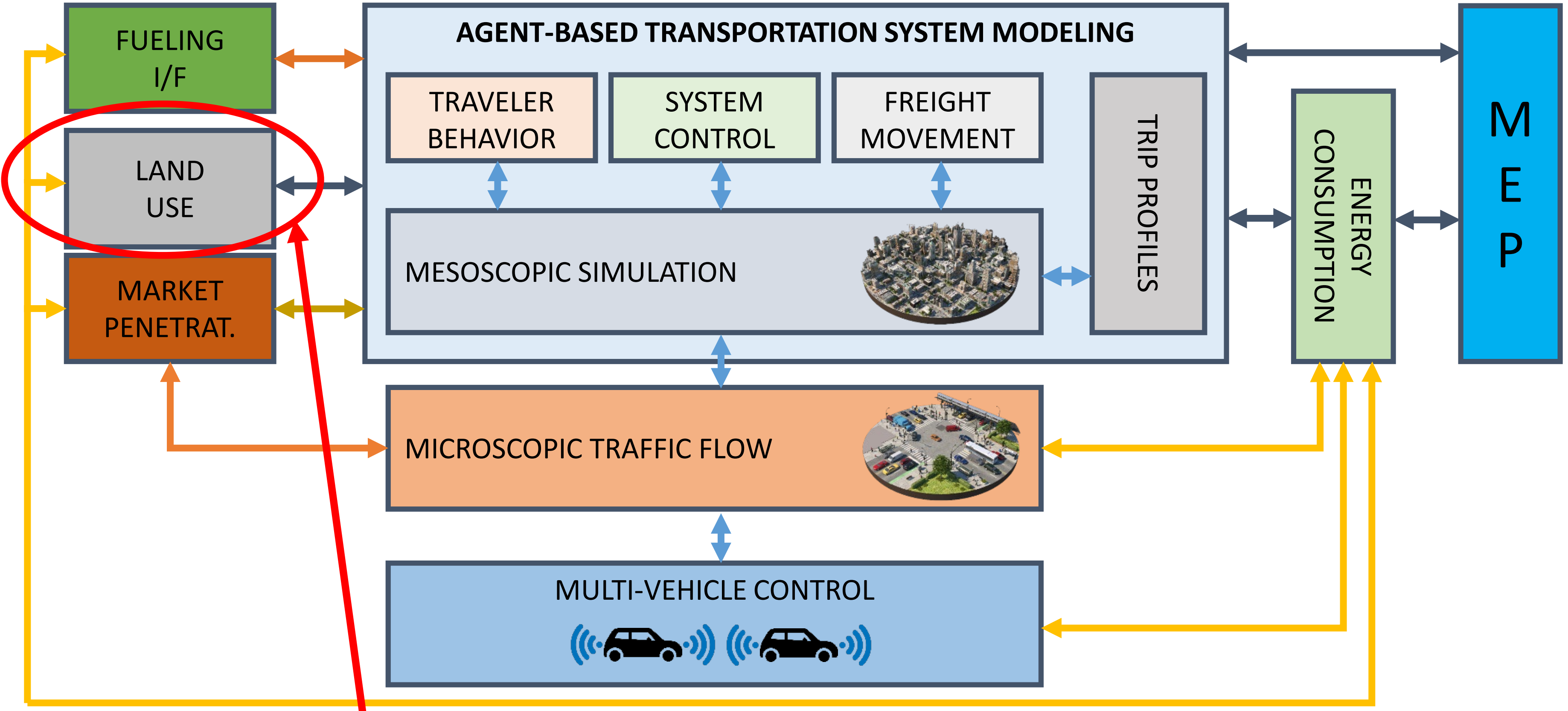
Land Use Change

Charging Siting & Operations



Advanced Accessibility Analysis

END-TO-END MODELING WORKFLOW



UrbanSim is the *only* land use model in the SMART Mobility workflow and is thus path-critical for most core models
US 2.2.2 is synonymous with the linkage between land use and agent based travel models

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

- UrbanSim application from MTC updated to interface with BEAM
- ActivitySynth: a new set of models to create person-level activity plans needed as inputs to BEAM, along with UrbanSim outputs
  - Workplace Choice
  - Auto Ownership
  - Work Arrival Time
  - Work Duration
  - Primary Mode to Work

Initial models completed
Validation in progress
Need to incorporate generalized time
Run time is approximately 25 minutes

  - School Choice
  - School Arrival Time
  - School Duration
  - Primary Mode to School

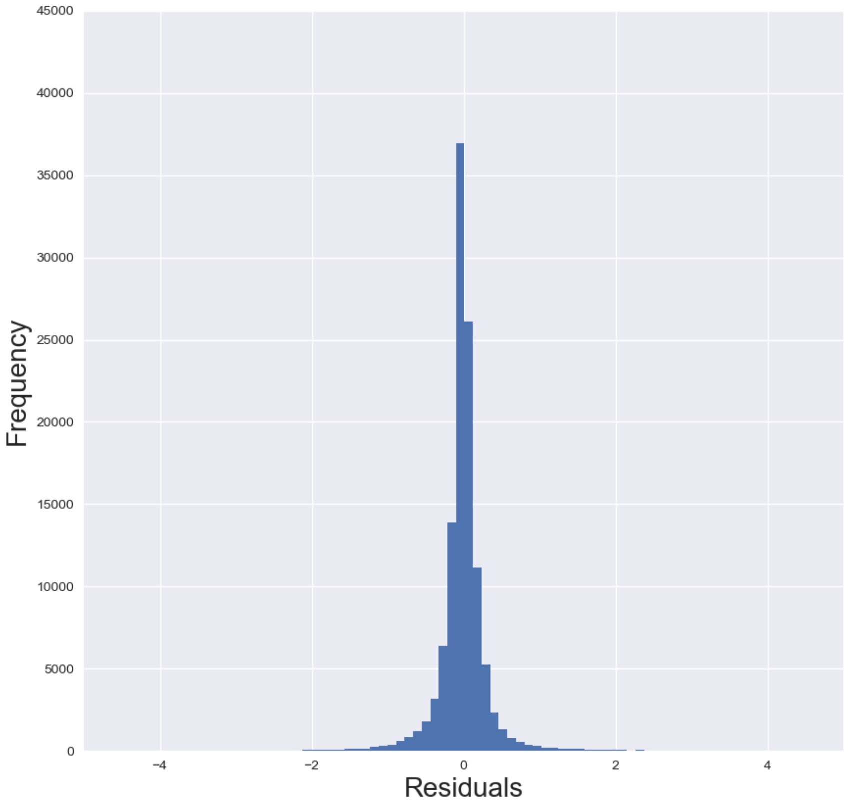
In progress

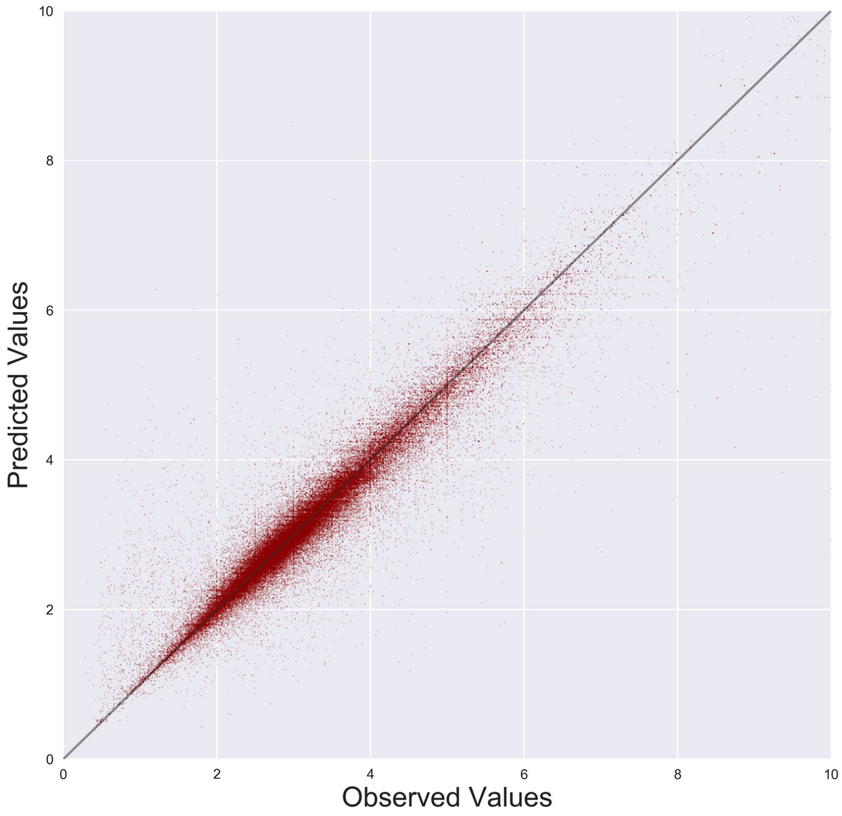
  - Discretionary Activity Destination, Mode and Schedule

Future

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

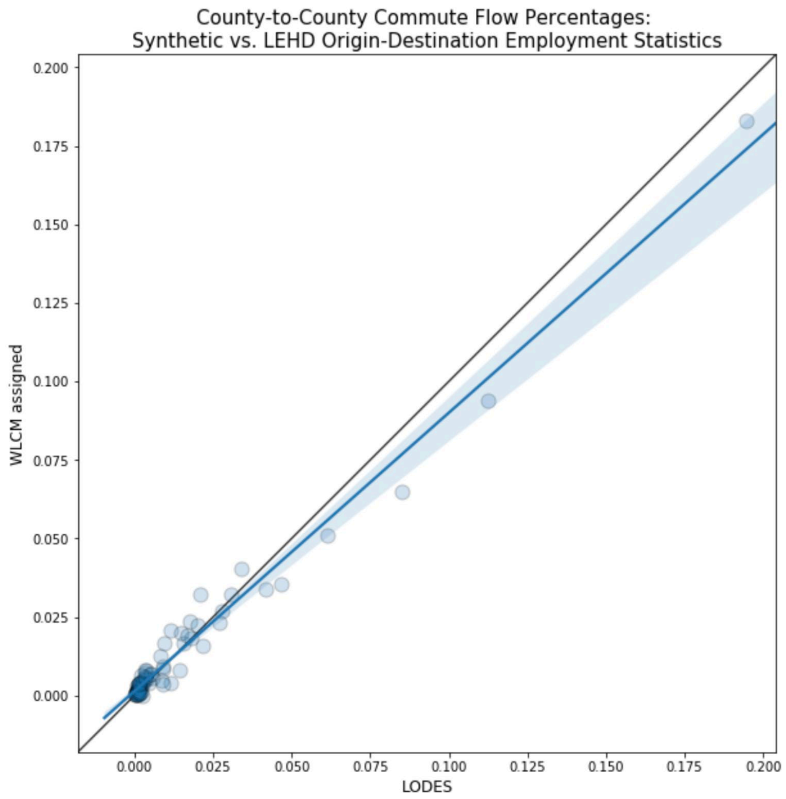
Hedonic Rent Model Validation: Good fit to Observed Data

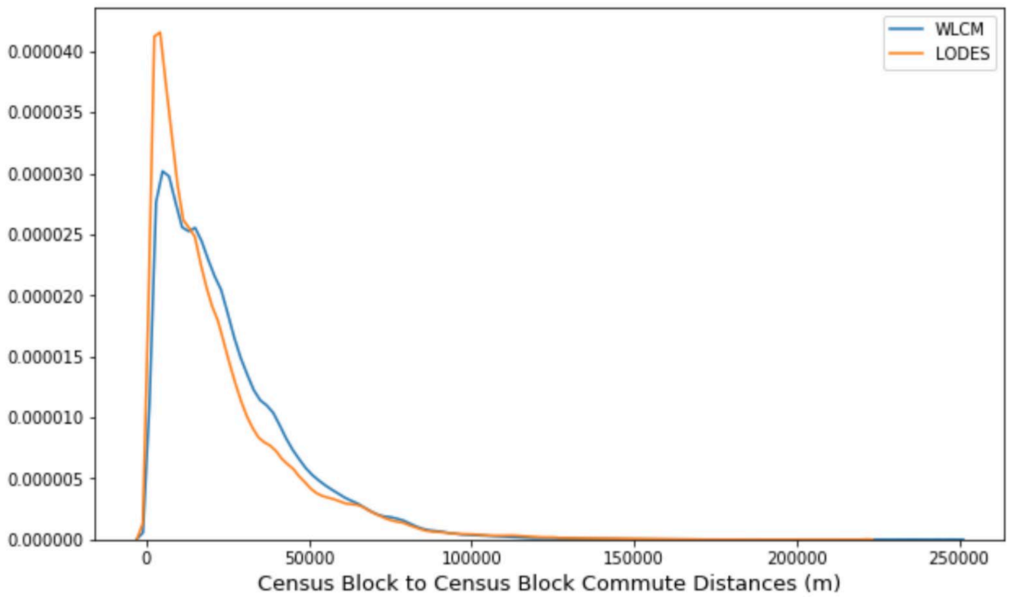




TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Workplace Choice Model Validation: Good fit to Observed Data





TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Home-Work Time of Day and Work Dwell Time: Good fit to Observed Data

ACTUAL

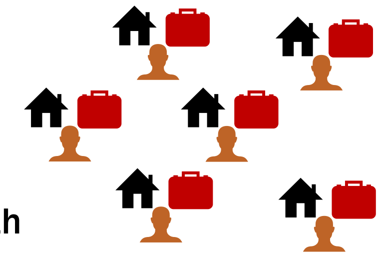
dwell_work TOD	0-4.5h	4.5-7.75h	7.75-9h	9-10.5h	10.5+h
3-6am	0.002118	0.004904	0.018336	0.023798	0.023017
6-9am	0.028981	0.086886	0.196511	0.222872	0.074514
9am-3:30pm	0.057515	0.089227	0.075573	0.040907	0.011704
3:30-6:30pm	0.011537	0.013041	0.003957	0.001505	0.001839
6:30pm-3am	0.002619	0.001616	0.003567	0.001560	0.001895

SYNTHETIC

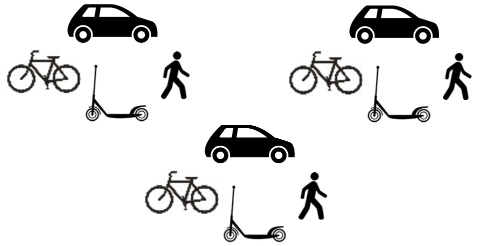
dwell_work TOD	0-4.5h	4.5-7.75h	7.75-9h	9-10.5h	10.5+h
3-6am	0.002309	0.004949	0.018818	0.022057	0.020727
6-9am	0.023975	0.076909	0.182807	0.224346	0.074691
9am-3:30pm	0.058283	0.097557	0.085253	0.047959	0.012358
3:30-6:30pm	0.012866	0.014255	0.004750	0.001804	0.001598
6:30pm-3am	0.002607	0.001677	0.004182	0.001598	0.001665

BEAM INTEGRATION

UrbanSim + ActivitySynth



BEAM



UrbanSim+ActivitySynth computes:

- **Home Location**
- **Work Location**
- **School Location**
- **Auto Ownership**
- **Modes**
- **Schedules**
- **Accessibility**

BEAM Computes:

- **Routes**
- **Optionally Modes**
- **Congested times**
- **Costs**
- **Generalized costs**

Baseline Plans →

← Baseline Skims

Revised Baseline Plans → Baseline Final

→ Scenario A Final

2025 Plans →

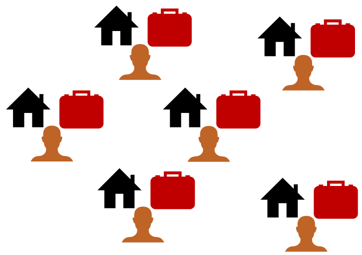
← Scenarios B & C Skims

2040 Plans → Scenario B Final

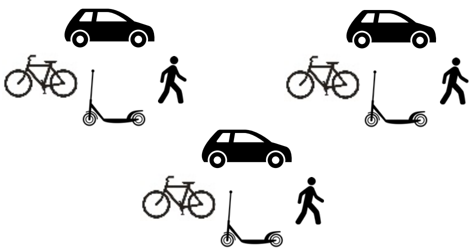
→ Scenario C Final

BEAM INTEGRATION: COMBINED RUN TIMES ARE AN ISSUE

UrbanSim + ActivitySynth



BEAM



UrbanSim+ActivitySynth
Benchmarks

100% sample:
7.5 million people
2 million parcels

Run times per Year
UrbanSim:
20-25 minutes

ActivitySynth:
25 minutes

Baseline Plans →
← Baseline Skims
Revised Baseline Plans →
2025 Plans →
← Scenarios B & C Skims
2040 Plans →

BEAM
Benchmarks

8% sample:
0.75 million people

72K Nodes
196K Edges

Run times per Year (Day)
24-48 hours

RUN TIME CHALLENGES

Ideally the land use and travel models would be coupled at least every 5 years

Using 5 year steps for a 2010 – 2050 run of one scenario would require:

< 9 hours for UrbanSim and ActivitySynth (using 100% sample)
9 – 18 days for BEAM (using 8% sample)

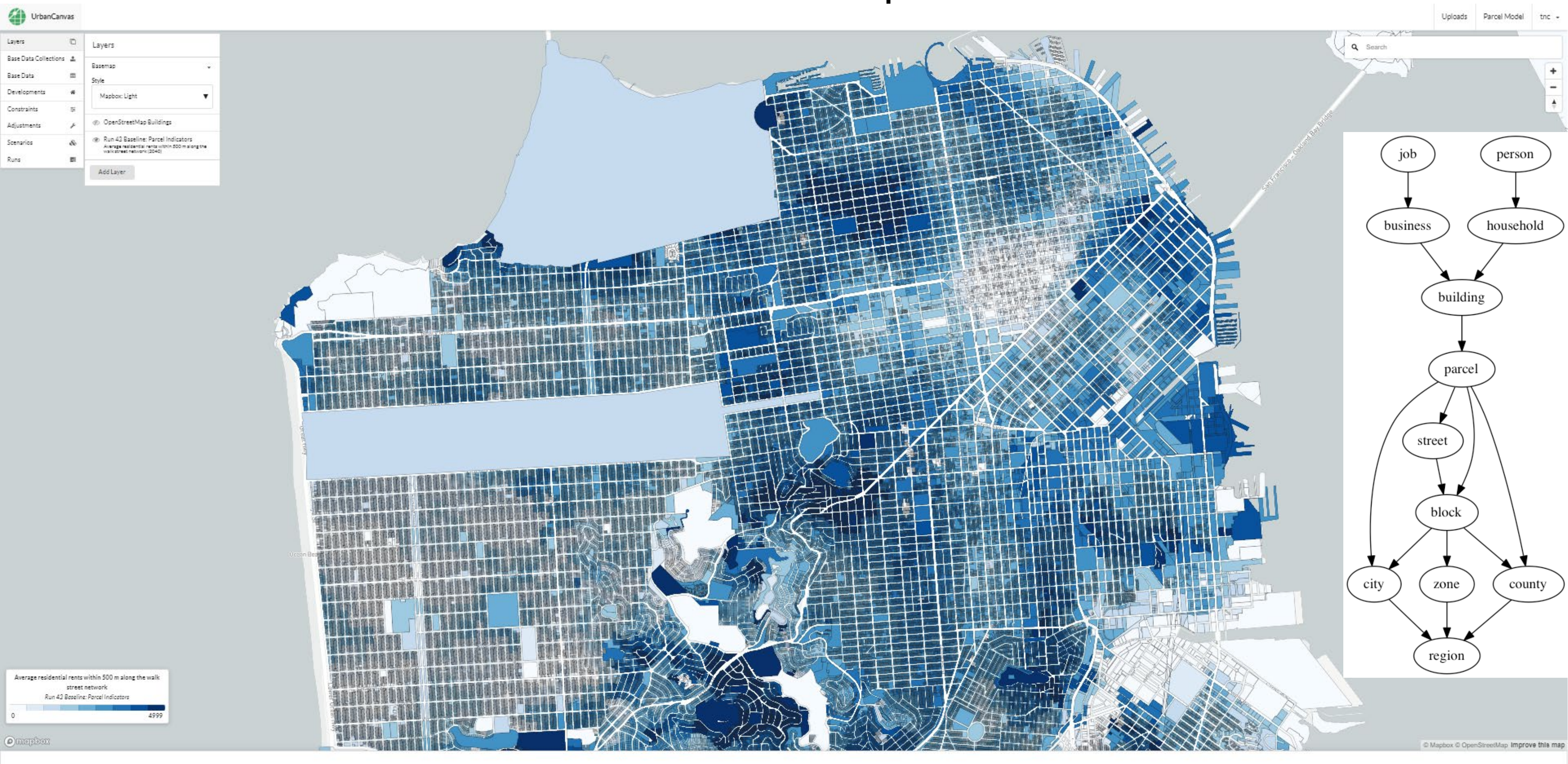
Run times for POLARIS are similar or longer

There is a need for deep software engineering, modularization and performance improvement in the network modeling components of the integrated models, along the lines undertaken for UrbanSim and ActivitySynth

Motivation for exploring collaboration on other network modeling components

FAST CUMULATIVE OPPORTUNITY ACCESSIBILITY METRICS

UrbanSim Pandana Library Computes Accessibility With a Connected Graph of the Metropolis
200K+ node walk scores compute in 1 second



NETWORK MODELING

Network modeling seems to be the largest computational bottleneck for the SMART Mobility agenda for integrated modeling. Our project is leveraging collaboration to experiment with options to accelerate performance and improve empirical realism that might benefit the broader SMART Mobility ecosystem.

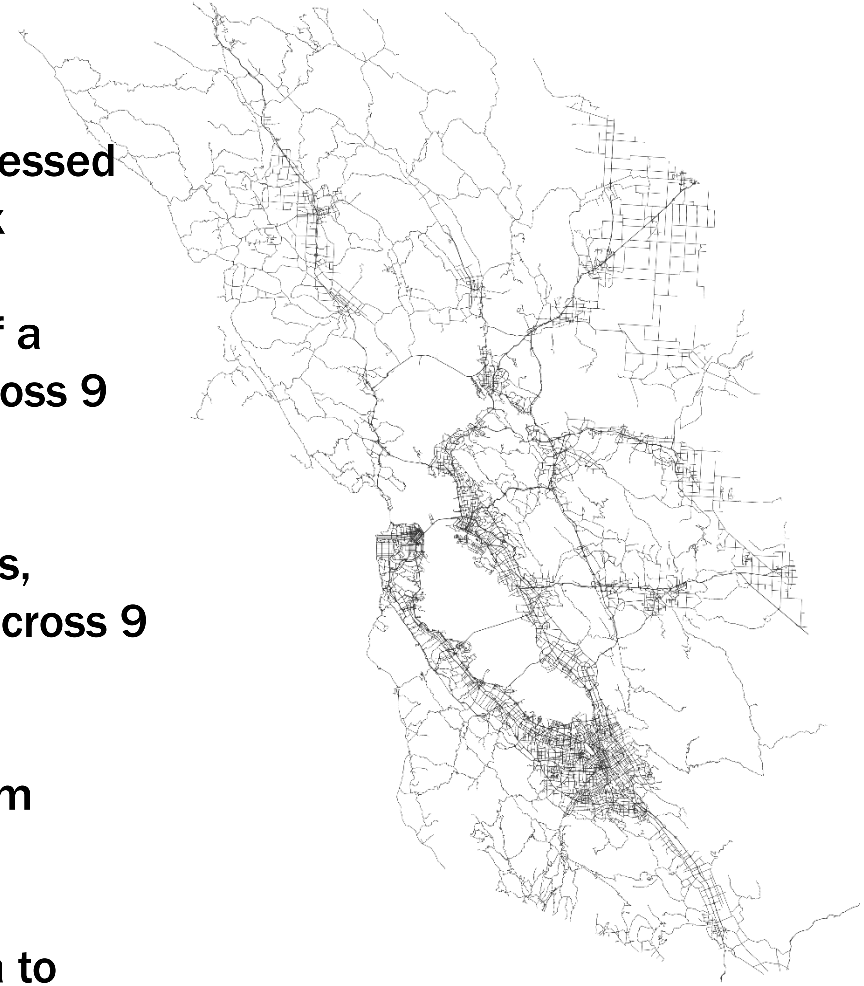
1. **Aggregate, Static** (collaboration with LBL HPC)
   - Static user equilibrium using Frank-Wolfe algorithm
   - Routing: shortest path based given demand
   - Results: volumes, speeds on each link

2. **Dynamic, Mesoscopic**
   - BEAM/MATSIM (LBNL collaboration)
   - POLARIS/TRANSIMS (ANL collaboration)
   - CB-Cities (UC Berkeley/UT Austin collaboration)
   - Results: volumes, speeds on each link

3. **Microsimulation** (TrafficSim-GPU, collaboration with Purdue, Google)
   - Routing individual vehicles using car following, lane changing
   - Acceleration, deceleration
   - Results: individual vehicle routes, volumes, speeds on each link, fuel consumption and pollution

NETWORK MODELING

- Road network models created and processed from OpenStreetMap data using OSMnx
- *Full network*: quarter million nodes, half a million edges, 53,000 km of streets across 9 counties (two-way encoding)
- *Simplified BEAM network*: 72,000 nodes, 196,000 edges, 20,000 km of streets across 9 counties (one-way encoding)
- Calculate BPR coefficients per edge from public data and imputation
- Convert zone-based travel demand data to network node-based



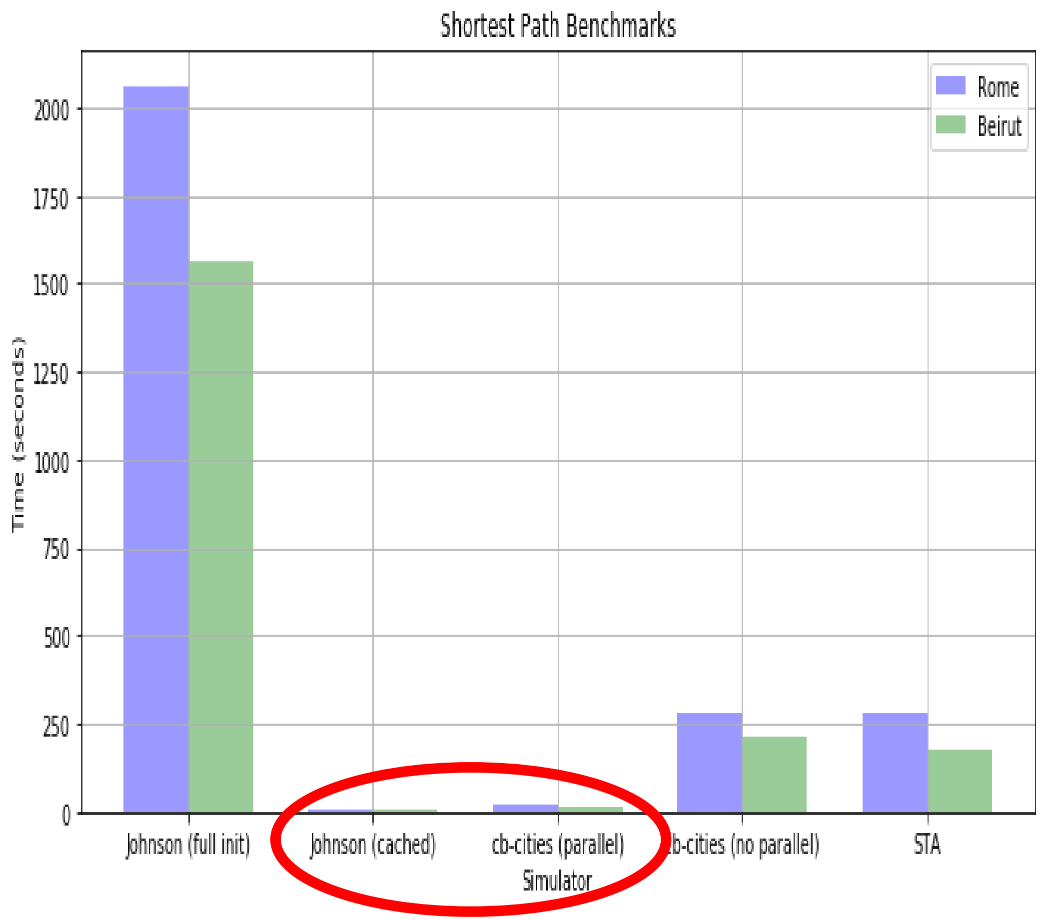
NETWORK MODELS

Shortest Path Benchmarks

Network is the tertiary Bay Area network with 31,121 nodes and 66,082 edges, with MTC data of 792,910 OD pairs and 1,843,894 people in total

Representing 8:00-9:00am with The full population of commuters traveling at peak hour

Some extremely fast options to accelerate routing component



RESPONSES TO PREVIOUS YEARS REVIEWERS COMMENTS

The reviewer commented that performance and runtime improvements, testing on multiple street networks, testing multiple traffic assignment suites, and code repository to run at scale are all appropriate future research, but quantitative metrics for these would be helpful in evaluating the effectiveness of the project.

We agree: we endorse a rigorous benchmarking of all project components, both empirical validity and computational performance. Additional performance benchmarks are included in this presentation.

The reviewer remarked that this project supports DOE's objectives by exploring the relationship between urban development and mobility, and it does so by using some known models (UrbanSim, ActivitySim), integrating them, and then addressing their deficiencies in either processing speed or validation against data. Because of this approach and the modular nature of the model architecture, it appears to the reviewer that this project promises to have more impact and to produce more useful insights than the other projects they have seen.

We appreciate the reviewer's perspective on this and agree that modularization and rigorous testing and refinement offer the best path for rapid innovation and impact.

RESPONSES TO PREVIOUS YEARS REVIEWERS COMMENTS

The reviewer graded these resources as "insufficient" because the funds going to this work seem fairly low compared to some of the other projects reviewed. Because of the clarity of vision that this project team seem to have, it appears that additional resources might be productively applied, more so than some others.

Resources were increased from $260K in FY18 to $430K in FY19 (of which $150K + $50K admin goes to BEAM project and LBNL and significant carryover from FY18 was subtracted). The goals of the project could be advanced more effectively with higher funding, but we have also made efficient use of the resources allocated and have leveraged collaborations heavily.

The project team needs to plan its future work more carefully and describe it more fully.

This point is well taken. Last year was the first year for the project and the first review. We have now mapped out in greater clarity a pathway for improving the models and making them practically applicable to many metropolitan areas.

COLLABORATION AND COORDINATION WITH OTHER INSTITUTIONS

BEAM/MEP Integration	• LBNL • ANL • NREL
Network Modeling	• UC Berkeley Urban Analytics Lab • UC Berkeley Civil and Environmental Engineering • University of Texas at Austin • Purdue University • Google
Urban Data Science Toolkit	• UrbanSim
Bay Area UrbanSim	• Metropolitan Transportation Commission (MTC)

REMAINING CHALLENGES AND BARRIERS

- Computational performance improving but still a substantial bottleneck
  - UrbanSim+ActivitySynth are not a bottleneck at this point
  - 1-2 days for BEAM runs with sampling is still very long per year; need to run every N years at 1-2 days per run
  - Limits capacity to run and compare scenarios
  - Limits capacity to assess uncertainty
- Discretionary travel model component still a significant gap
- ActivitySynth models need additional refinement and validation
- UrbanSim models need additional refinement and validation
- Combined model system needs additional testing: sensitivity, scenarios
- Challenges for scaling model system to many metropolitan areas
  - Data, Modularity, Flexibility, Local Adaptation
- Challenges for making the model system practically useful for MPOs, DOTs
  - Deployment, Usability for planners

PROPOSED FUTURE RESEARCH

- Software engineering to increase modularity, flexibility, pace of innovation to support full SMART Mobility research agenda
  - leverage new UrbanSim Template library for model components
  - Leverage Pandana and UrbanAccess in implementing efficient MEP metrics
- Software engineering to increase computational performance
  - Alternative algorithms for key bottlenecks in model system
  - Network modeling/routing components a primary focus
- Refinement of model specifications, calibration, validation
  - UrbanSim
  - ActivitySynth
  - Network models
- Extensive testing and evaluation of full combined model system with BEAM/MEP
- Detailed assessment and planning for scaling up
  - Data, model development pipeline, adaptability of models
  - Usability and deployment

SUMMARY SLIDE

- Integrating land use with transportation models enables more realistic assessment of cumulative impacts of transportation innovations on energy consumption, travel, and urban development patterns
- Integrated modeling requires effective software engineering for modularity, performance, rapid innovation
- Impact of project will come from scaling and broad adoption by MPOs, DOTs and others

Credit: https://commons.wikimedia.org/wiki/File:Liding%C3%B6bron_October_2015_03.jpg

QUESTIONS?

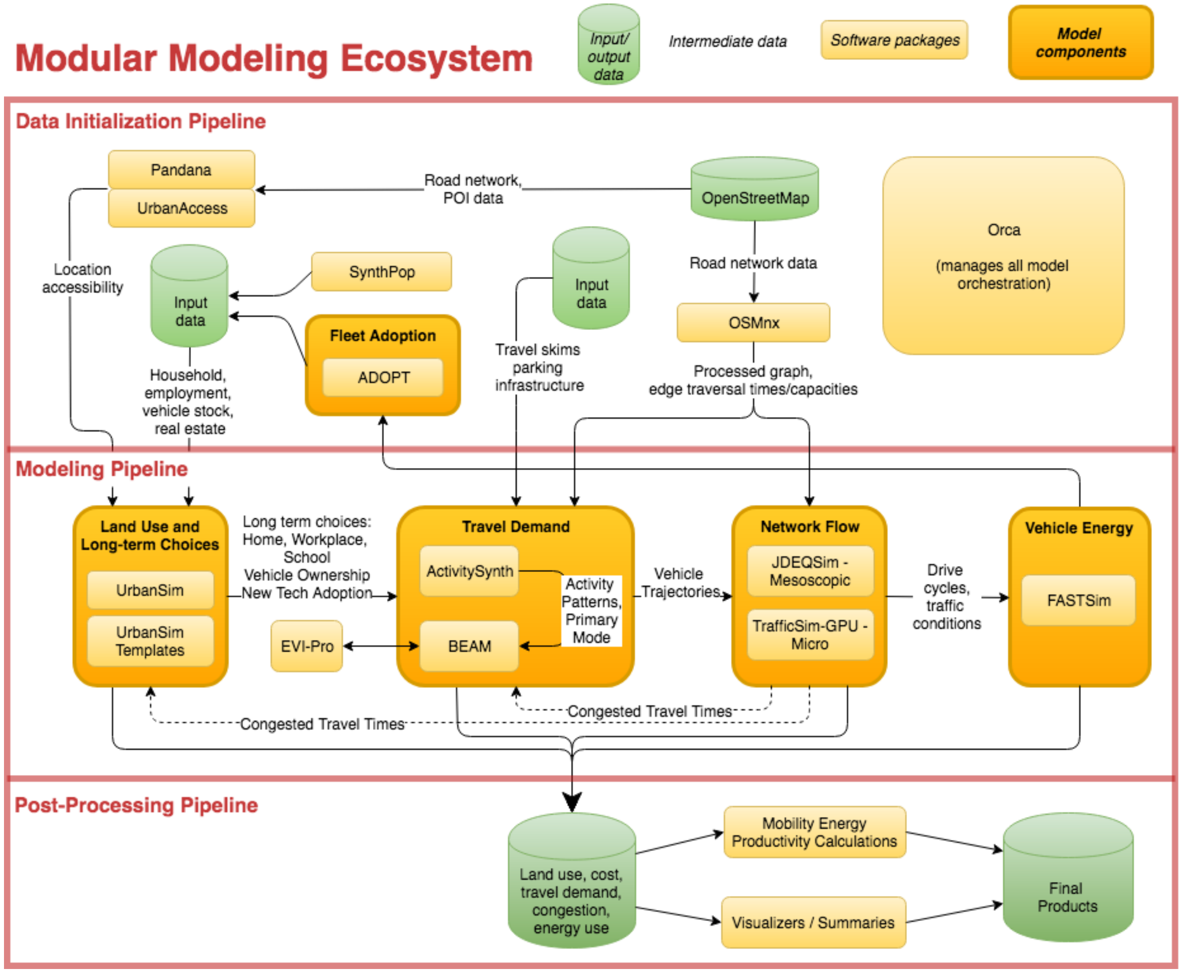
TECHNICAL BACK-UP SLIDES

APPROACH

The vision for this project is to create a foundation for broad integration and software modularity across SMART models, enabling rapid innovation and advancement of research program.

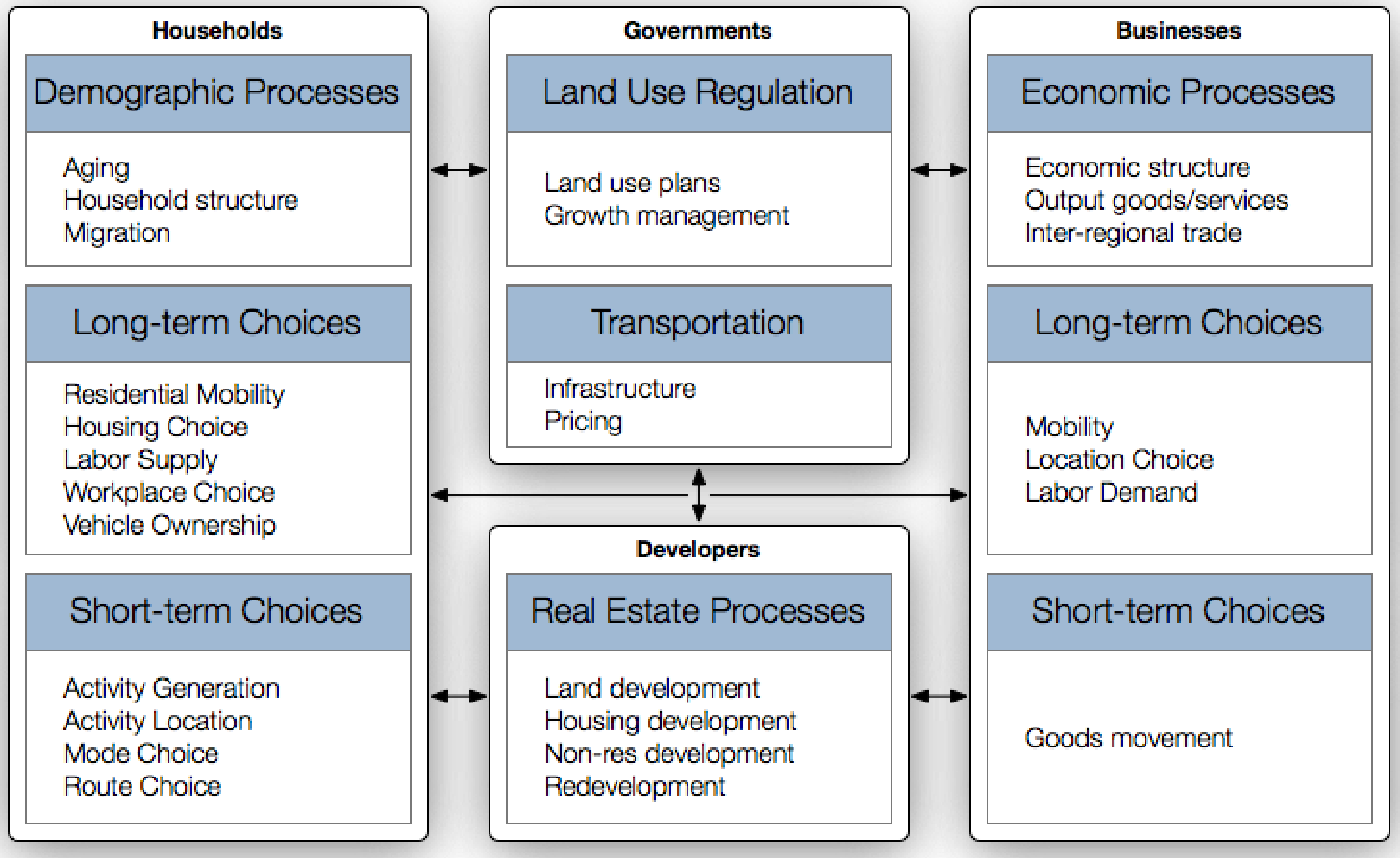
This project contributes many key open source components:

- **OSMnx** (network processing)
- **Pandana** (access computations)
- **UrbanAccess** (transit access)
- **SynthPop** (population synthesis)
- **Orca** (simulation orchestrator)
- **UrbanSim** (long-term models)
- **UrbanSim Templates** (modules)
- **ActivitySynth** (activity generation)
- **TrafficSim-GPU** (microsimulation)



APPROACH

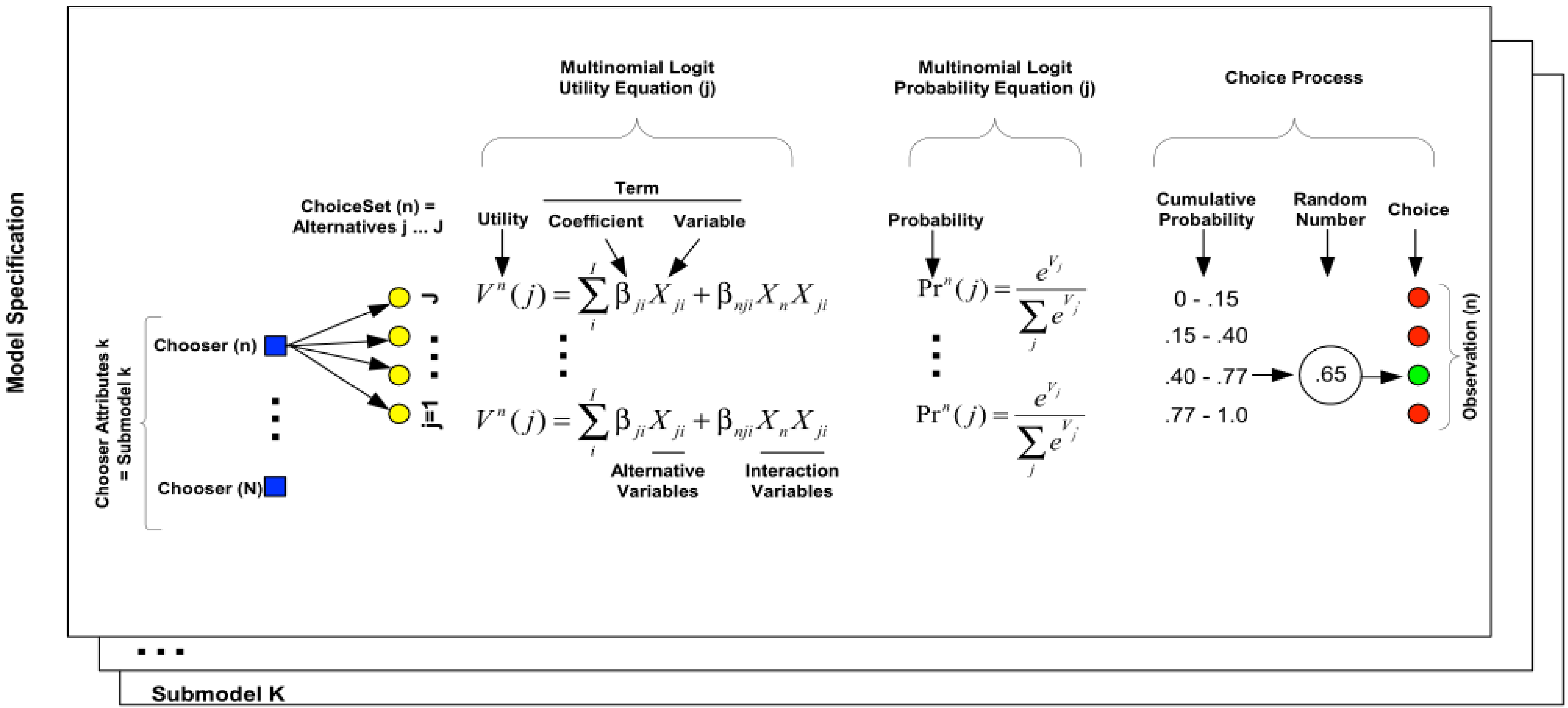
UrbanSim Microsimulates Choices of Households, Businesses, Developers



APPROACH

UrbanSim Microsimulates Choices of Households, Businesses, Developers

Models choices such as household location, for entire populations, at an agent level



TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Workplace Choice Model

- Pseudo $\bar{R}$^2 : 0.5
- Predicts matching of individual workers from residence location to workplace
- Parcel level of geography
- Accounts for:
  - Education interacted with employment sector of job
  - Multi-modal travel time, cost and distance (to be revised using generalized time for BEAM integration)
  - Validates well on predicted commute trip length distribution

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Auto Ownership Model

- $\bar{R}^2$: 0.314
- Choices:
  - No vehicles, 1 vehicle, 2 vehicles, 3 or more vehicles
- Auto ownership increases with household income, size, and number of workers
- Single-family households are more likely to have more vehicles
- Decreases with number of children
- Households in denser areas are less likely to own any vehicles

Auto Ownership Model: Validation

Columns: Actual
Rows: Predicted

```
validate.model_crosstab(m2)
```

_alt_id	0	1	2	3
_choices				
0	0.059270	0.404928	0.408149	0.127654
1	0.045976	0.348478	0.449953	0.155592
2	0.042662	0.318573	0.466490	0.172275
3	0.044469	0.303244	0.473000	0.179287

```
validate.tp_rates(m2)
```

	0	1	2	3	all
True Positive rate	0.05927	0.348478	0.46649	0.179287	0.303037

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Home-Work Trip End Time (Arrive at Work Time)

- $\bar{R}$^2 : 0.433
- Time of Day Categories:
  - 3-6am, 6-9am, 9am-3:30pm, 3:30-6:30pm, 6:30pm-3am
- Minorities are more likely to arrive at work in the earliest or latest time of day categories
- Likelihood of going to work early or late is inversely related to household income and education level
- People 16-25 years of age are more likely to arrive at work after 9am
- Women are more likely to arrive at work between 6am and 3:30pm
- One-person households, households without a vehicle, and rented households are more likely to generate midday trips to work
- Job sector influences work start time

Work Dwell Time

- $\bar{R}^2$: 0.160
- Dwell Time Categories (hours):
  - 0 to 4.5, 4.5 to 7.75, 7.75 to 9, 9 to 10.5, 10.5 and above
- Women are more likely to work for less time
- Minorities are more likely to work over 7.75 hours
- People in the manufacturing, retail, transportation, information, finance, science and technology, healthcare, and government sectors are less likely to work short hours
- Work dwell is inversely related to education level and household income

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Home-Work Mode Choice

- $\bar{R}^2$: 0.624
- Mode Choice Categories:
- Drive Alone, Shared Ride, Walk to Transit, Drive to Transit, Bike, Walk
- Men are more likely to drive and walk
- The likelihood of driving decreases with education level and increases with the number of household vehicles
- Minorities are more likely to drive to transit and less likely to bike or walk
- The likelihood of walking to transit decreases with income but the likelihood of biking, walking, or driving to transit increases with income
- Bigger households and people with more than one job are more likely to walk to transit, bike, or walk, and less likely to drive to transit

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

Home-Work Mode Choice: Validation

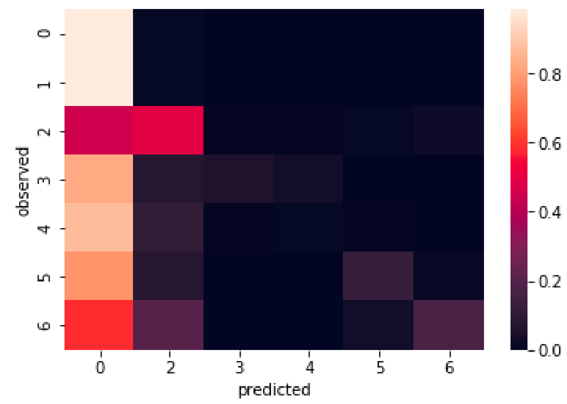
0: Drive Alone
1: Carpool
2: Walk to Transit
3: Drive to Transit then Walk
4: Walk to Transit then Drive
5: Bike
6: Walk

```
validate.model_crosstab(m) # normalized by index
```

predicted	0	2	3	4	5	6
observed						
0	0.981719	0.012348	0.001443	0.000481	0.002566	0.001443
1	0.984848	0.012626	0.000000	0.000000	0.002525	0.000000
2	0.453629	0.493952	0.004032	0.006048	0.014113	0.028226
3	0.830645	0.076613	0.056452	0.036290	0.000000	0.000000
4	0.872146	0.105023	0.004566	0.013699	0.004566	0.000000
5	0.780919	0.074205	0.003534	0.000000	0.123675	0.017668
6	0.585366	0.201220	0.000000	0.000000	0.036585	0.176829

```
sns.heatmap(validate.model_crosstab(m))
```

<matplotlib.axes._subplots.AxesSubplot at 0x7fdd947d0630>




```
# Validation process
from scripts import validate
validate.tp_rates(m)
```

	0	1	2	3	4	5	6	all
True Positive rate	0.981719	0	0.493952	0.0564516	0.0136986	0.123675	0.176829	0.801791

Home-School Trip End Time (School Arrival Time)

- $\bar{R}^2$: 0.348
- Time of Day Categories:
  - 3-7:45am, 7:45-8:30am, 8:30-9:30am, 9:30am-3pm, 3pm-3am
- Children in elementary school are more likely to arrive at school from 7:45-8:30am
- The likelihood of arriving at school later increases with age
- Women are more likely to arrive at school before 7:45am
- The likelihood of arriving at school before 7:45am is inversely related to household income
- Households without a vehicle and with less than 4 people are more likely to generate school trips that end from 8:30-9:30am

TECHNICAL ACCOMPLISHMENTS AND PROGRESS

School Dwell Time

- $\bar{R}^2$: 0.348
- Dwell Time Categories (hours):
  - 0 to 3.5, 3.5 to 6, 6 to 8, 8 to 10, 10 and above
- Children 12 to 16 years old are more likely to spend over 6 hours in school
- Minorities are less likely to spend less than 3.5 hours in school
- School dwell time increases with education level and household income

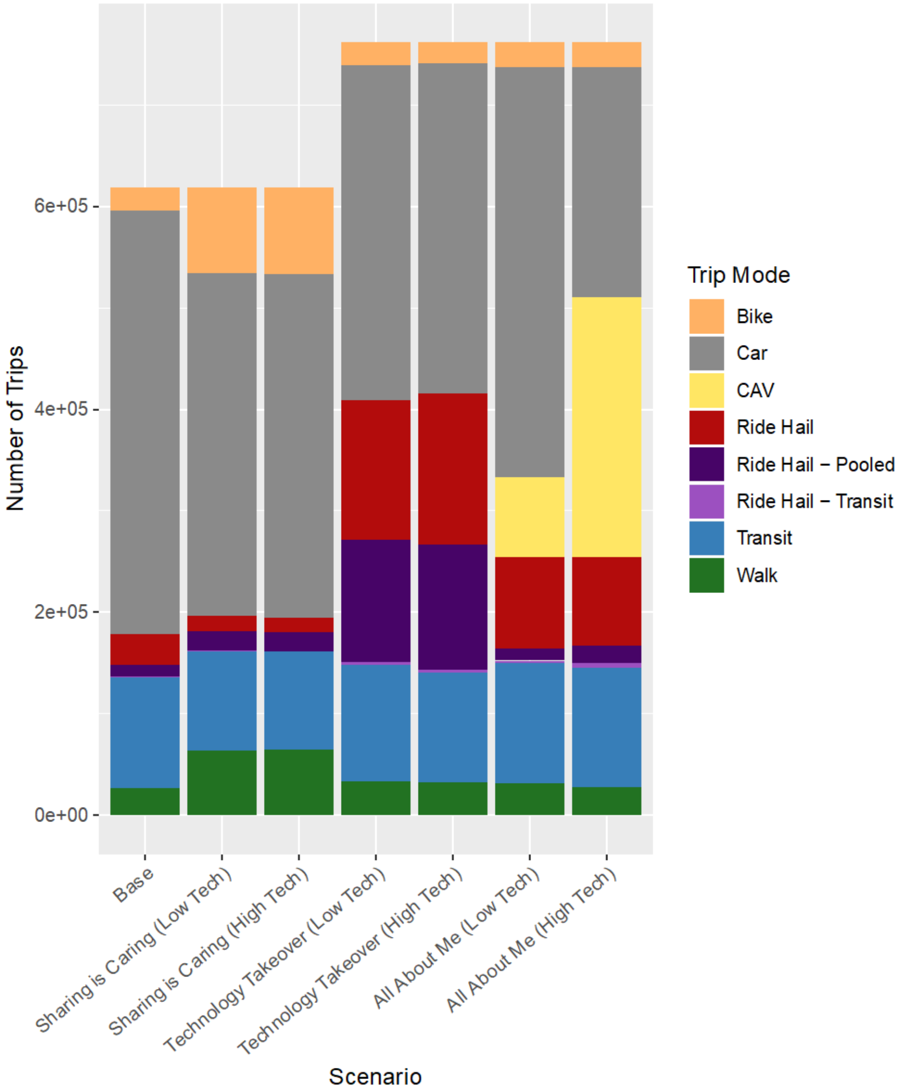
SMART Common Scenarios

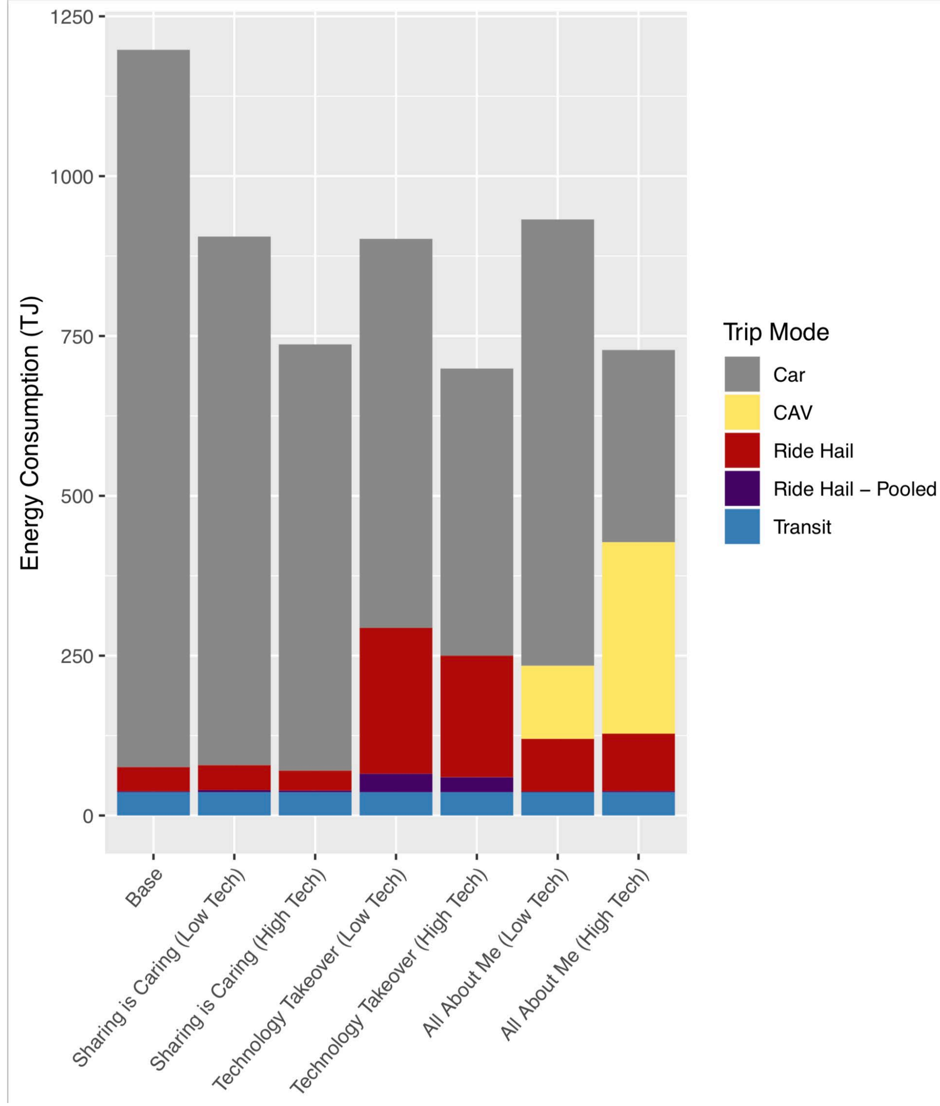
		Sharing is caring	Technology Take-Over	All about Me
Variables	**Baseline**	**High sharing low automation**	**High tech - mobility**	**Low sharing high Automation**
Market Penetration (CAV)	Baseline	Low	High	High
Automation Level	Baseline	Med	High	High
Private Ownership	Baseline	Low	Low	High
Shared Use - commerical	Baseline	High	High	Low
VOTT (Car mode only)	Baseline	High	Low	Low
Propensity non-car modes	Baseline	High	Low	Low
E-Commerce	Baseline	High	High	Low
Long Haul Commodity Flow	Baseline	Baseline	High	High
Vehicle Technology (Energy, Cost…)	Baseline	Mid Term Low Tech & Mid Term High Tech	Long Term Low Tech & Long Term High Tech	Long Term Low Tech & Long Term High Tech

Scenarios

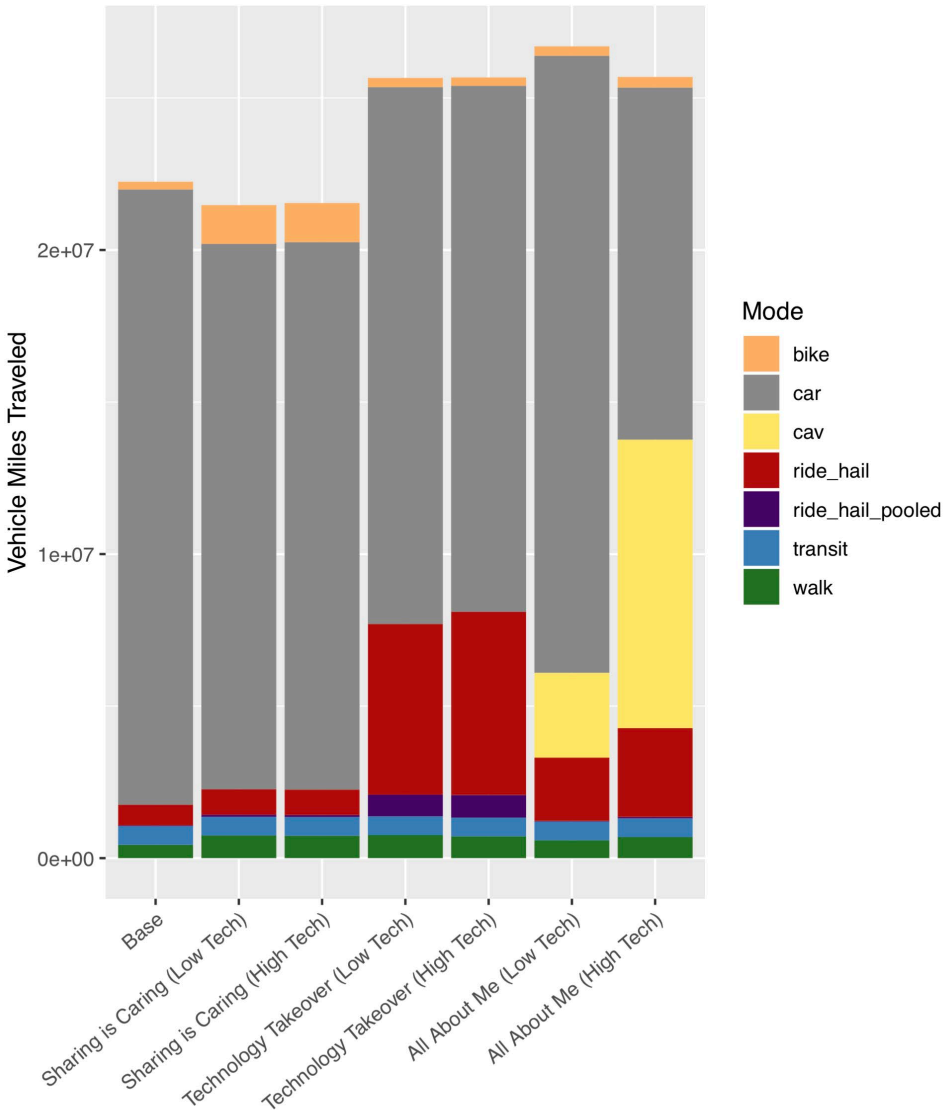
- A - High Sharing Low Automation - New technology (e.g., integrated apps) enables people to significantly increase use of transit, car sharing and multi-modal travel. Low vehicle automation (e.g., CACC) is being introduced mainly on highway system
- B – High Technology Mobility – Technology has reshaped mobility enabling a high usage of ride pooling and multi-modal trips as they are convenient and inexpensive. Private ownership thereby decreases. Telecommuting is common, and e-commerce trend escalated
- C – Low Share with High Automation – Fully automated vehicles with significant market penetration, especially in households. Ability to own AVs yields low telecommuting, low e-commerce and more urban sprawl

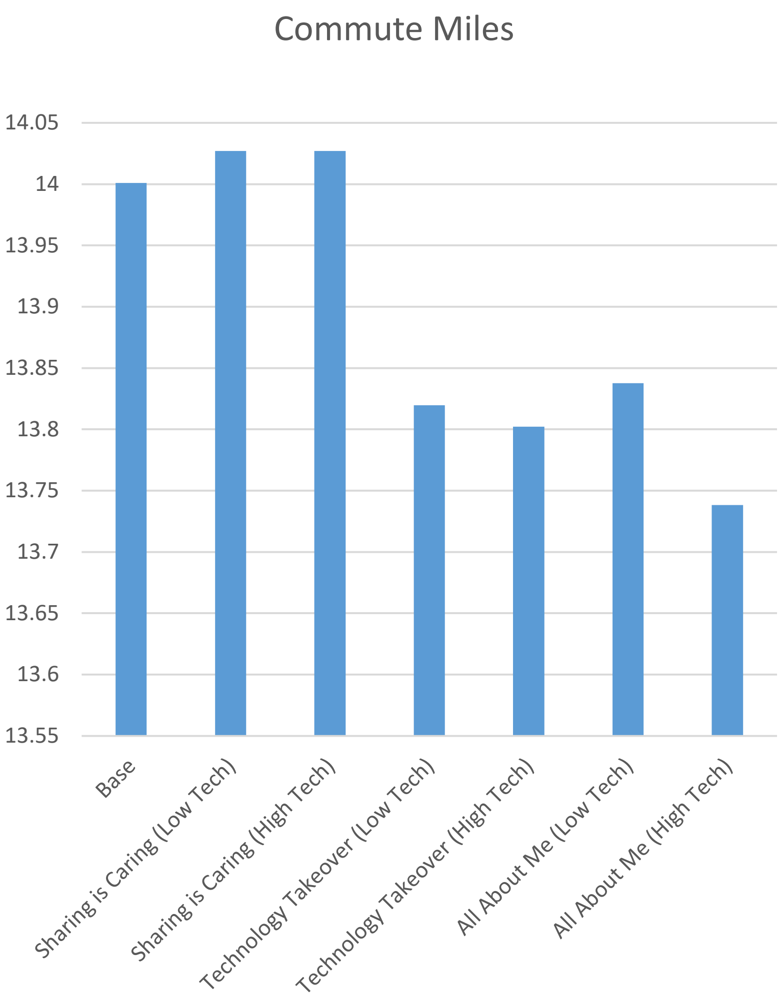
RESULTS: URBANSIM + BEAM





RESULTS: URBANSIM + BEAM





NETWORK MODELING

Static Traffic Assignment (Collaboration with LBNL HPC)

- Macroscopic in nature - considers all vehicles as a flow moving through the network
- User equilibrium (Wardrop's first principle / Nash equilibrium)
  - Selfish routing as users minimize their individual travel times
- Social equilibrium (Wardrop's second principle)
  - Cooperative routing in which total travel time in the network is minimized
- Comparable to full microsimulation run
  - Computes shortest path
  - Runs Frank-Wolfe until the edge impedances converge (iterative root-finding method)

NETWORK MODELING

Urban Analytics Lab GPU Microsimulator (Collaboration with Google, Purdue)

Ignacio Garcia Dorado, Paul Waddell, Daniel Aliaga

- Fast traffic microsimulation that includes:
  - Per-vehicle simulation
  - Lane changing
  - Car following
  - Gap acceptance
  - Intersection modeling
- Traffic atlas framework - make locations of adjacent cars on an edge map to contiguous bytes of memory

From I.G. Dorado's "GPU Detailed Traffic Microsimulation of a Massive Road Network"

NETWORK MODELING

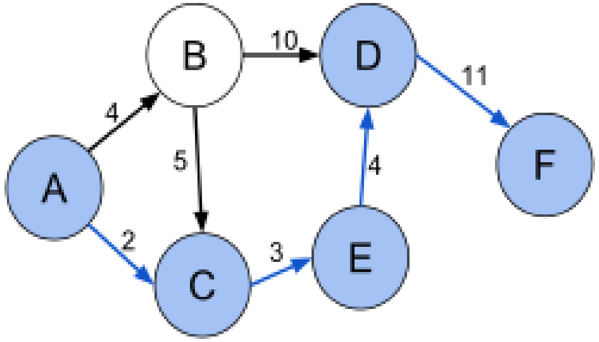
Routing

- Johnson’s shortest path algorithm

- Initial iteration computes shortest path for all OD pairs
  - Does APSP - works well due to sparse graph
  - O(VElogV)
  - Keeps all-to-all matrix in RAM
  - RAM required (in GB) = n^2 * 8 bytes / 10^9 (e.g. 30K nodes ~ 7 GB RAM, 225K nodes ~ 400 GB RAM)

- The number of vehicles whose shortest paths are updated gradually reduces after initial iteration (linear after initial calculation)

- Runs in CPU



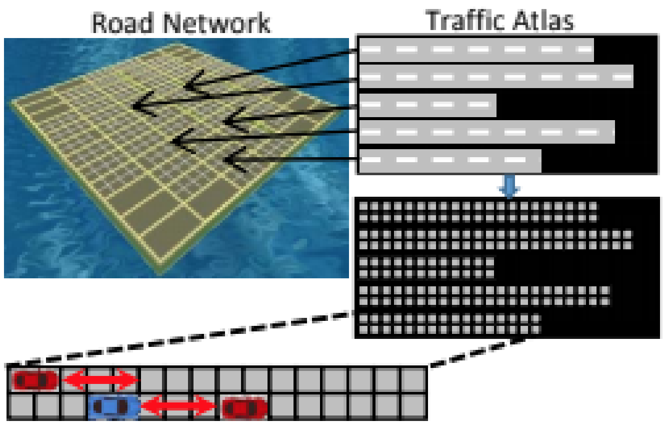
NETWORK MODELING

Microsimulation

$$\dot{v} = a\left[1 - \left(\frac{v}{v_o}\right)^{\delta} - \left(\frac{s^*(v,\Delta v)}{s}\right)^2\right]$$

$$m_i = \begin{cases} \exp(-(x_i - x_0)^2) & x_i > x_0 \\ 1 & x_i \le x_0 \end{cases}$$

- Car Following
- Lane Changing
- Gap Acceptance
- Each car at each time step computes:
  - New speed, acceleration, position
  - For speed and acceleration, the car checks the traffic atlas (contiguous bytes from current position) to find the position and speed of surrounding cars
- Example: given the car's position, the car might stay in the current edge or it may move to the following edge
- Runs on GPU



Traffic Atlas.
From I.G. Dorado's "GPU Detailed Traffic Microsimulation of a Massive Road Network"

NETWORK MODELING

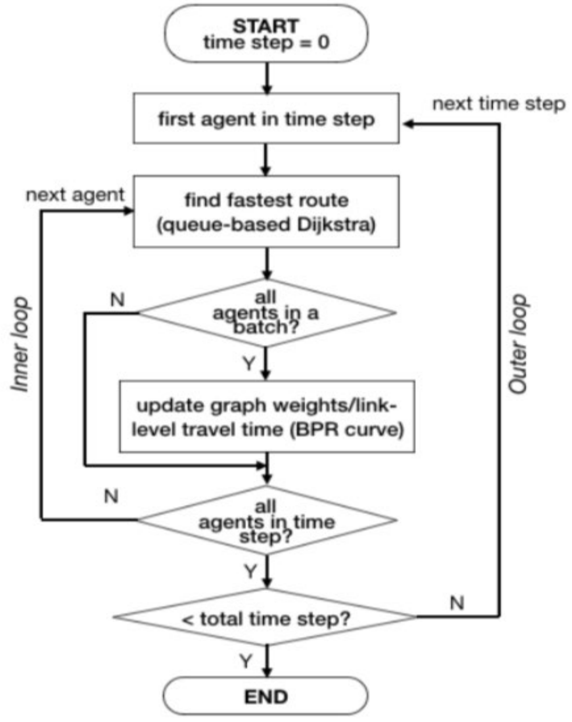
Intersection Modeling (ongoing)

- All intersections were assumed to have traffic lights initially
- Intersection first updated, then the cars are updated
- Initially, only one road's cars can move at any timestep
- Which lanes connect to which lanes on each edge at an intersection
- Types:
  - Traffic lights
  - Pass through (motorway junction)
  - Stop sign
  - Roundabout (turning circle)

NETWORK MODELS

cb-cities (activity based model with mesoscopic simulation)
Collaboration with Kenichi Soga group – UC Berkeley/UT Austin

- Agent-based macroscopic traffic simulator (for the Bay Area)
- Based on simplified assumption of volume-delay relationship between flow and average speed (greater efficiency than microscopic rules)
  - Link volume from initial weights from graph in t0 -> calculate speed at t0 -> use t0 speed to run shortest path in t1
- Dijkstra priority queue shortest path algorithm
  - Shortest distance from one node (source) to every other node (SSSP)
  - Executed for each OD pair at every time step
  - The weights don't change within a batch of the iterative process the choice of route for an agent is not affected by the route assignment of other agents
  - This allows for parallel Dijkstra computation for agents in the same batch



From B. Zhao et al. "Agent-Based Model (ABM) for City-Scale Traffic Simulation: A Case Study on San Francisco."